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Kubitza, Christoph; Krishna, Vijesh V.; Klasen, Stephan; Kopp, Thomas; Nuryartono, Nunung; Qaim, Matin

Veröffentlichungsversion / Published Version
Zeitschriftenartikel / journal article

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Empfohlene Zitierung / Suggested Citation:
Kubitza, C., Krishna, V. V., Klasen, S., Kopp, T., Nuryartono, N., & Qaim, M. (2024). Labor Displacement in Agriculture: Evidence from Oil Palm Expansion in Indonesia. *Land Economics*, *100*(3), 547-567. https://doi.org/10.3368/le.100.3.122122-0109R1

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https://nbn-resolving.org/urn:nbn:de:0168-ssoar-95834-6

Labor Displacement in Agriculture: Evidence from Oil Palm Expansion in Indonesia

Christoph Kubitza *Research Fellow, German Institute for Global and Area Studies, Hamburg, Germany; christoph.kubitza@giga-hamburg.de*
Vijesh V. Krishna *Lead Economist, International Maize and Wheat Improvement Center, Hyderabad, India; v.krishna@cgiar.org*
Stephan Klasen *Professor, Department of Economics, University of Goettingen, Germany. Deceased October 2020.*
Thomas Kopp *Professor, School of Economic Disciplines, University of Siegen, Germany; thomas.kopp@uni-siegen.de*
Nunung Nuryartono *Professor, Department of Economics, Institut Pertanian Bogor, IPB University, Bogor, Indonesia; nuryartono@apps.ipb.ac.id*
Matin Qaim *Professor, Center for Development Research, University of Bonn, Germany; Institute for Food and Resource Economics, University of Bonn, Germany; mqaim@uni-bonn.de*

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ABSTRACT *We analyze the labor market effects of oil palm cultivation among smallholder farmers in Indonesia. Oil palm requires less labor per unit of land than alternative crops, especially less female labor. Microlevel data and nationally representative regency-level data show that oil palm adoption, on average, led to an expansion of total cropland at the expense of forestland, resulting in higher agricultural labor demand for men. At the same time, women's employment rates declined due to a substantial decrease in agricultural family labor, which was most evident in regions with high initial land scarcity and thus limited options for cropland expansion.* (JEL O13, Q15)

1. Introduction

Empirical research has shown that growth in agricultural productivity substantially contributes to overall economic growth (McArthur and McCord 2017), poverty reduction (Christiaensen and Martin 2018), and reduced global pressure on forestland (Villoria 2019). Productivity enhancements in agriculture are also necessary to keep labor in the sector, given that in many countries the share of agriculture in total value added remains well below the agricultural labor share (Emerick 2018). In high-income countries, technical change has largely contributed to closing this gap, as the diffusion of labor-saving technologies has led to a multifold increase in labor productivity. The diffusion and structural effects of labor-saving technologies are well documented in these countries (Sunding and Zilberman 2001; Gallardo and Sauer 2018). For developing countries, on the other hand, evidence is scarce, and economic conditions are likely to differ from the historical trajectories of high-income countries. Still, labor-saving technologies—such as mechanization and herbicide application—are often perceived as key technologies to increase agricultural labor productivity in developing countries (Haggblade et al. 2017; Sheahan and Barrett 2017; Adu-Baffour, Daum, and Birner 2019).

It is widely recognized that labor savings in agriculture can have heterogeneous effects on different strata of rural societies and depend on the level of aggregation (Pingali 2007; Haggblade et al. 2017). Increasing labor productivity can directly boost profits at the farm level. At larger scales, such as the village or district level, the effects are more ambiguous. Higher labor productivity can translate into higher incomes for agricultural laborers. Moreover, if sufficient income is generated in the agricultural sector, local demand effects can increase employment rates and wages

Land Economics • August 2024 • 100 (3): 547–567
DOI:10.3368/le.100.3.122122-0109R1
ISSN 0023-7639; E-ISSN 1543-8325
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across other sectors as well. Conversely, a labor-saving technology will reduce labor demand if wages and output stay constant. A lower labor demand in agriculture, or an oversupply of labor in the nonagricultural sector through farm households reallocating saved labor time, can displace individuals with limited access to production factors or lower labor productivity.[1]

Labor-saving technologies or land uses can increase income inequality, deepen poverty, and eventually even foster civil unrest, but detailed empirical evidence on the underlying mechanisms is surprisingly scarce in developing countries' rural areas at larger scales. A few studies focus on direct productivity effects, income gains, cropland expansion, and labor savings (Benin 2015; Adu-Baffour, Daum, and Birner 2019; Kirui 2019). Yet most studies do not empirically analyze the wider labor market effects (Bouwman, Andersson, and Giller 2021; Caunedo and Kala 2021). Several reasons might explain the scarcity of evidence. First, at larger scales, the spread of labor-saving technologies is often difficult to assess because of limited data availability. Second, the adoption of labor-saving technologies in the past was often restricted to large agricultural companies or relatively small groups of larger farms.

This article contributes to the literature by analyzing the wider labor market effects of the labor savings introduced by the expansion of oil palm in Indonesia. The boom of the palm oil sector in Indonesia is related to targeted government interventions and large-scale acquisitions of concessions by transnational investors as well as the widespread use of contract farming schemes around the world (Lay et al. 2021). In response, global production of palm oil rose by around 600% between 1990 and 2016, with Indonesia being the largest producer (Byerlee, Falcon, and Naylor 2017; U.S. Department of Agriculture 2017). Owing to differences in labor intensity and productivity between oil palm and alternative cash crops, oil palm expansion was found to increase the living standard of oil palm adopters and agricultural laborers (Euler et al. 2017; Bou Dib et al. 2018; Gehrke and Kubitza 2021).[2]

To define a technology or practice as labor-saving, it is necessary to know which production system it replaces. Following the literature on oil palm cultivation and welfare, we argue that oil palm can be characterized as labor-saving in that it requires less labor per unit of land than the dominant alternative crops in the regions, such as rice and rubber. For labor-saving technologies, output is the same, but the technology has changed such that less labor is required. These new technologies can also be understood as a new way of allocating production factors to increase technical efficiency on the farm. A labor-saving land use certainly goes beyond just reorganizing production factors; however, primary data show that in comparison to competing land uses, one of the major effects of oil palm expansion is the significant decrease in labor intensity. We find no convincing evidence for oil palm being skill-biased or for unobserved patterns in agricultural production significantly changing due to oil palm expansion that in turn directly influence labor displacement. Migration flows and infrastructure development might change due to oil palm expansion, but we control for these alternative explanations in the latter sections of the article. Oil palm is interesting because it is not only grown by large companies but to a substantial extent by smallholder farm households. In 2019, smallholder farm households cultivated more than 40% of the national oil palm area in Indonesia (Chrisendo, Siregar, and Qaim 2022), and nonfarm households in rural areas also derived substantial income from working on oil palm farms (Bou Dib et al. 2018). Yet like the more general criticism of labor savings in agriculture, research also emphasizes the potentially adverse effects of oil palm expansion on the welfare of landless and other marginalized strata of rural society (Cramb and Curry 2012; Obidzinski et al. 2012; Li 2015).

[1] Although this article focuses on labor markets, higher agricultural productivity is also likely to decrease commodity prices and increase the welfare of consumers.

[2] Oil palm is a tropical plant that produces fruit bunches containing oil-rich mesocarp. Palm oil is extracted from the mesocarp and then further processed into various edible and nonedible products.

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A few studies have already analyzed the economic effects of oil palm expansion in Indonesia to study long-term demographic changes (Gehrke and Kubitza 2021) and poverty reduction (Edwards 2019a). Examining the effect of oil palm expansion on poverty since the 2000s, Edwards (2019a) finds a significant reduction in poverty and indirect effects on rural and social infrastructure, applying a similar identification strategy as we do here. This study, however, does not focus on labor savings introduced by oil palm or on potential labor displacement. It is solely based on a regency-level panel from secondary data, not microlevel household data. Gehrke and Kubitza (2021) focus on the effects of the oil palm expansion on changes in demographic patterns and find significant reductions in fertility. Their study is also mostly based on a regency-level panel from secondary data and focuses on the theoretical and empirical determinants of long-term demographic changes. Although we use similar identification strategies proposed by Edwards (2019a) and Gehrke and Kubitza (2021), this study is unique because of its combination of new data at different scales (household and regency levels) as well as its focus on labor savings in agriculture and their effects on labor displacement. These aspects were not analyzed in depth in the existing literature to the best of our knowledge.

The second contribution of this article is the analysis of the employment effects of labor savings in agriculture with respect to cropland expansion. If the initial labor supply is the limiting factor, labor savings allow for cropland expansion and increases in output. Land expansion could mitigate the initial drop in demand for agricultural labor per unit area. If growth in agricultural output and income increases local demand, growth in other rural sectors is also likely to occur. Such aspects have not been extensively considered in the existing empirical research on the effects of labor savings in agriculture, particularly when it comes to the role of smallholder farmers in oil palm cultivation. These factors may play an important role in Indonesia, as oil palm cultivation is often linked to cropland expansion, deforestation, and degradation of natural ecosystems (Butler and Laurance 2009; Koh et al. 2011; Carlson et al. 2018; Chrisendo, Siregar, and Qaim 2021). For large-scale palm oil investments, recent studies already evidence positive local spillovers, such as increases in labor and total factor productivity of manufacturing plants not related to palm oil value chains (Kraus, Heilmayr, and Koch 2021) and improved public infrastructure (Edwards 2019b; Kraus, Heilmayr, and Koch 2021).

How does a labor-saving innovation, such as the adoption of oil palm, affect welfare and employment in the rural labor market?[3] The widespread adoption of oil palm by smallholder farmers, constant returns to skill, and significant changes in labor intensity provide the unique opportunity to pin down the wider labor market effects of labor savings in agriculture. To guide our analysis, we focus on two major options for farm households to reallocate the labor time saved through oil palm adoption, which may have heterogeneous welfare and equity effects. First, the saved time may be reallocated to the off-farm sector. Second, more labor is used to enable cultivation of additional cropland.[4] In the empirical analysis, we use different data sources, such as local household data collected during several surveys and representative national survey data from 2000 to 2015. In addition, we use land cover data from satellite imagery. Our identification strategy to tackle the potential endogeneity of oil palm adoption builds on fixed-effects models and an instrumental variable (IV) approach. For our local household data, we use a three-round panel dataset with village- and household-level fixed effects. For the national panel with regency-level observations, we rely on regency-level fixed effects and an IV based on the variability in regencies' suitability for oil palm cultivation.

[3] Unlike the body of literature that exists on the long-run structural effects of labor savings in agriculture (Clark 1940; Lewis 1954; Lagakos and Waugh 2013; Bustos, Caprettini, and Ponticelli 2016; McArthur and McCord 2017), we focus on short- and medium-term impacts, namely, those related to the displacement of labor.

[4] Increasing labor intensity per unit area is hardly an option, since labor requirements in oil palm cultivation are relatively fixed with production technology. In addition, oil palm is a cash crop that is traded internationally, so increases in output do not lead to falling prices locally. For nontradable commodities, higher productivity would lower output prices leading to different effects (Collier and Dercon 2014).

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2. Conceptual Framework

We assume that once the necessary infrastructure, such as palm oil mills and roads are in place, the decision to adopt oil palm is mainly based on individual preferences and constraints of farm households. Recent work shows that the positive income effect of oil palm cultivation is partly driven by lowering the labor intensity compared with competing crops (Rist, Feintrenie, and Levang 2010; Euler et al. 2017).[5] Appendix Table A1 illustrates, based on plot data, the differences in intensity and productivity between oil palm and rubber from a survey in Jambi Province in Sumatra (Gehrke and Kubitza 2021). Labor productivity is significantly higher in oil palm compared with rubber. Other studies confirm the relatively higher labor productivity in oil palm compared with rice cultivation (Rist, Feintrenie, and Levang 2010). Male labor hours per hectare and per year are 72% lower for oil palm compared with rubber cultivation. For women, the labor hours decrease even more dramatically, by 92%, since considerable additional physical strength is needed to harvest oil palm compared with rubber (Mehraban et al. 2022). Women are hence often restricted to maintenance work and collecting loose oil palm fruits (Koczberski 2007; Li 2015). We further observe that women receive lower wages in oil palm than men. Although we cannot calculate gender differences in agricultural productivity owing to the joint management of plots, we interpret the changes in working hours and wages comparing oil palm and rubber as showing a relatively lower labor productivity of women in oil palm cultivation compared with men.

Estimates in Appendix Table A1 alongside findings of other studies suggest that oil palm has a lower land productivity compared with competing crops, especially rubber (Rist, Feintrenie, and Levang 2010; Euler et al. 2017). However, if the opportunity costs of family labor, which are important for more labor-intensive cropping systems, are included when calculating farm profits, oil palm is more profitable (Grass et al. 2020). Based on this evidence, we assume that at least some part of the positive income effect is derived from reallocating labor to additional cropland or the nonagricultural sector (Krishna et al. 2017a).[6] Gehrke and Kubitza (2021) provide further evidence on labor savings introduced by oil palm adoption.

Farm Household Scale

To derive testable hypothesis, we consider a typical agricultural household model in which a household maximizes utility from the consumption of services and goods and leisure:

$$\max_{q,L} U(q,L;K), \tag{1}$$

where q is the vector of quantities of services and goods, L denotes the household's time allocated to leisure, and K represents the household characteristics. The time constraint faced by the household is given by

$$T = T_F + T_A + T_{NA} + L, \tag{2}$$

where T is the total time endowment,[7] T_F denotes family labor hours deployed on the own farm, T_A represents labor hours deployed off-farm in agricultural employment, and T_{NA} denotes labor hours in nonagricultural employment.

We assume a simplified budget constraint at the farm household level to illustrate the effects of a labor-saving land use change (Goodwin and Holt 2002):

$$pq + r'X = A\ P_a f\{T_F, X\} + w_A T_A + w_{NA} T_{NA}, \tag{3}$$

where p represents the price of services and goods. X is a vector of farm input quantities, the price vector of which is r. A refers to farm size, and the revenue is generated according to the production function f per land unit using family labor T_F and farm inputs X. P_a is the

[5] PODES (Indonesian village survey) data show that rubber and rice are the main competing crops of oil palm at the village level in Indonesia.

[6] Palm oil is a highly demanded export product. We assume a high elasticity of the final demand.

[7] Note that T is constrained by the available family labor.

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output price for agricultural good. w_A and w_{NA} are the wages for off-farm work in the agricultural and nonagricultural sector, respectively.[8]

To represent the reality on the ground, as captured by the descriptive statistics in Appendix Table A1 and findings in the existing literature, we make the following four assumptions with respect to our model. First, labor productivity increases compared with competing crops at low levels of labor input: $\partial f(OP)/(\partial T_F) > \partial f/(\partial T_F)$, where $f(OP)$ is production per unit of farmland A that is allocated to oil palm. Second, the amount of land per unit of labor in efficiency units is decreasing. Thus, the marginal product of labor in oil palm falls more rapidly with an increasing number of hours worked per unit area compared with competing crops (Bustos, Caprettini, and Ponticelli 2016).[9] Third, owing to the additional physical strength needed in oil palm cultivation, the relative labor productivity of men increases compared with women: $(\partial f(OP)/\partial T_{F,M})/(\partial f/\partial T_{F,M}) > (\partial f(OP)/\partial T_{F,W})/(\partial f/\partial T_{F,W})$. The subscripts W and M denote the labor allocation of women and men, respectively. Fourth, we assume that wages in agriculture are a function of labor productivity and increase with oil palm expansion in the short run: $w_A(OP) > w_A$, where $w_A(OP)$ is the wage obtained in employment in oil palm cultivation. From this, it follows that agricultural wages for men increase more strongly owing to their relatively higher labor productivity in oil palm compared with women: $w_{A,M}(OP)/w_{A,M} > w_{A,W}(OP)/w_{A,W}$.

In the following, we outline the expected effects of oil palm adoption at the farm household scale for land-scarce and land-abundant settings. If land is scarce (A is fixed), given that not all farm households have access to additional land (Krishna et al. 2017b), our first and third assumptions suggest that $T_{F,W}$ and $T_{F,M}$ decrease with oil palm adoption, with $T_{F,W}$ decreasing more dramatically than $T_{F,M}$. Farm households can increase their incomes by allocating their freed labor time to the off-farm sector, thus increasing T_{NA} and T_A. Given free movement of labor between sectors and a competitive labor market, $w = \partial f P_a / \partial T_F$ in the long run. As the relative labor productivity of women in oil palm cultivation is declining with increasing land dedicated to oil palm growing, we expect that women, particularly, opt to work in the nonagricultural sector, hence $T_{NA,W}$ increases.

In a land-abundant setting, freed labor can be reallocated to new cropland, hence A increases, potentially offsetting the initial decrease in T_F. This will particularly be the case if $\partial f(OP)P_a/\partial T_F > w$ in the short run. This outcome is more likely for men, as they have a relatively higher labor productivity in oil palm, although this may also apply to female household members.

The model further implies that with labor savings in agriculture, households might reallocate family labor hours deployed on farm T_F to leisure L, depending on the opportunity costs of each activity. We have argued that the positive income effects of oil palm adoption derive partly from the redistribution of labor to other productive uses. If saved labor is instead reallocated to leisure, income may not increase or, in the extreme case, even decrease. Yet a shift of all the labor saved to leisure is unlikely in the Indonesian setting where many of the households are relatively poor. Reallocating some of the labor to leisure would likely reduce the effects hypothesized here but not change the overall direction. Based on these considerations, we state the following hypotheses sets 1 and 2:

Hypotheses set 1. If land is scarce:

1.1. Oil palm adoption increases total income of farm households through additional off-farm employment.

1.2. Oil palm adoption decreases the likelihood to work in agriculture, particularly for

[8] We define off-farm work as including agricultural employment, nonagricultural employment, and self-employment. Note that we use the terms *off-farm* and *on-farm* in the case of land use change at farm scale. In the case of interpreting the effects at higher scales, we differentiate between the agricultural and nonagricultural sector.

[9] A technical change that increases labor productivity is labor-saving if the elasticity of substitution between land and labor is smaller than the land share of output (Bustos, Caprettini, and Ponticelli 2016), a condition that is likely to be satisfied in the context of agriculture.

women in farm households. This can be offset by off-farm employment.

Hypotheses set 2. If land is abundant:

2.1. Oil palm adoption increases total income of farm households through cropland expansion.

2.2. Oil palm adoption has limited impact on off-farm employment in farm households. Sectoral shifts between men and women may occur.

Aggregate Scale

At higher spatial scales, we expect more ambiguous labor market effects depending on the abundance of land. We follow the model by Gehrke and Kubitza (2021), which considers each regency to behave like a small open economy with two sectors and integrate our reasonings on effect heterogeneity based on land scarcity.[10]

Gehrke and Kubitza's (2021) model derives the general equilibrium effect of the oil palm expansion on wages as a combination of local economy and labor demand effects. First, regarding the local economy, the model concludes that the higher labor productivity in oil palm increases wages in agriculture, $w_{A,M}$, in particular for men (*productivity effect*).[11] Given that labor can move freely between sectors, all other wages would increase, too. Second, if oil palm adoption increases incomes because of higher labor productivity and land expansion, we expect an increasing demand for other local goods and services (Klasen, Priebe, and Rudolf 2013; Emerick 2018). This would increase wages in the nonagricultural w_{NA} (*local demand effect*). For labor demand effects, we expect that the demand for agricultural labor T_F decreases initially in particular for women due to their relatively lower labor productivity. In addition, lower labor demand in agriculture could decrease agricultural wages (*labor demand effect*). For land abundance, we consider that cropland expansion could dominate over the labor demand effect, leading to higher demand in agricultural labor, particularly for male labor.

In a scenario with land scarcity, we expect that a major part of the freed labor in the farm sector is allocated to the nonagricultural sector, hence T_{NA} increases. Since the market clearing condition in the nonagricultural sector is $w_{AN}=p_{AN}MPL_{AN}$, with p_{AN} being the output price of the nonagricultural good and MPL_{AN} the marginal product of labor in that sector, we expect that the additional supply of labor to the nonagricultural sector decreases wage rates in that sector (*labor supply effect*).[12] Which group of effects dominate, the labor demand and the labor supply effects or the productivity and the local demand effects, depends ultimately on the newly generated consumption demand and thus on the magnitude of the income increase from adopting oil palm.[13] At an aggregated scale, an oversupply of nonagricultural labor and decreasing labor demand in agriculture would depress wages and reduce employment opportunities.

In a scenario with abundant land, we expect that the saved labor from oil palm adoption would be reallocated to additional cropland, *A*. If the additionally cultivated land absorbs freed labor (hence no labor supply and no labor demand effect), we expect that oil palm expansion positively affects agricultural employment and the nonagricultural sector through local demand linkages and increases in agricultural labor productivity. However, even under land abundance, increases in the relative labor productivity of men could lead to a redistribution of labor activities between

[10] In the model, the agricultural sector produces goods that can be traded, whereas in the nonagricultural sector, production factors and the nonagricultural good are immobile.

[11] Recent studies on large-scale palm oil investments found increases in labor and total factor productivity of manufacturing plants not related to palm oil value chains (Kraus, Heilmayr, and Koch 2021) and improved public infrastructure (Edwards 2019b; Kraus, Heilmayr, and Koch 2021). This suggests that if smallholder oil palm expansion correlates with the expansion of large-scale estates, we would also expect increases in nonagricultural wages w_{AN}. We conduct a robustness check in the empirical part to test the relation between both production models.

[12] As long as the nonagricultural good is a nontradable.

[13] This effect partly also depends on the share of the additional consumption demand, which is satisfied by either local or foreign markets. We assume, however, that this ratio remains constant.

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Table 1
Datasets

	Year of Survey/Observation	Source
Local surveys		
Farm households[a]	2012; 2015; 2018	Primary data collected by authors
Spatial data		
Location of palm oil mills	1922–2022	Benedict et al. (2023)
Forest cover in Indonesia	2000; 2005; 2010; 2012	Margono et al. (2014)
Large-scale oil palm plantations	2000; 2005; 2010; 2015	Austin et al. (2017)
Max. attainable yield of different crops	1961–1990 (baseline data)	Global agro-ecological zones data
National surveys		
National labor force survey (SAKERNAS)	2000–2015	Badan Pusat Statistik
Tree Crops Statistics	2000–2015	Ministry of Agriculture
National village survey (PODES)	2001; 2003; 2006; 2011; 2014	Badan Pusat Statistik
Indonesian census	2000; 2010	IPUMS International database

[a] $n = 683$ per survey round.

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genders. Based on these considerations, the following impacts are possible in the case of land scarcity or land abundance (hypotheses sets 3 and 4):

Hypotheses set 3. If land is scarce:

3.1. Employment in agriculture decreases with oil palm adoption, especially for women. If the nonagricultural sector does not absorb all freed labor, total employment rates are likely to drop.

3.2. While the effect of oil palm on nonagricultural wages is ambiguous, it can be concluded that decreasing wages are an indicator of the labor supply and demand effects dominating the local demand and productivity effects.

Hypotheses set 4. If land is abundant:

4.1. Demand for agricultural labor will likely not decrease and may even increase, especially for men. Due to changes in relative labor productivity, women are likely to shift to the nonagricultural sector.

4.2. Agricultural and nonagricultural wages increase (based on 4.1).

3. Data

The empirical analysis employs data from different analytical levels, such as local household and national datasets, and from various sources, such as surveys and remote sensing. The local household data detail agricultural input and output for rubber and oil palm at the plot level and employment data for oil palm adopters and nonadopters at the household and the individual levels. These data were collected by the authors from a specific region (see details below), as the information is not readily available in national surveys. However, national surveys have larger sample sizes and provide regency-level panel data reaching back to the early 2000s. Using panel data for all of Indonesia enables us to apply a more refined identification strategy and observe the effects of oil palm expansion at broader scales. Table 1 lists the different datasets used in the analysis.

Primary data were gathered as part of an interdisciplinary project in Jambi Province, Sumatra (Kopp and Brümmer 2017). Jambi Province ranks sixth in national palm oil production in Indonesia (Kubitza et al. 2018). To establish a panel dataset, a household survey was conducted in 2012, 2015, and 2018. Sampling was based on a multistage framework and included 683 randomly selected farm households in 45 villages. Sampling details are explained by Kubitza et al. (2018). Since the survey partly included households relying on farming to a lesser extent, we drew a threshold at 1 ha, referring to all households above this threshold as farm households, reducing the sample size across all three waves from 2,051 to 1,874. Geocoded data on the locations of palm oil mills in Jambi Province

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for each year were obtained from Benedict et al. (2023).

National data were obtained from several sources. We included regencies (*kapubaten*) into our analysis and excluded cities (*kotas*), as oil palm expansion happens mainly in rural areas.[14] SAKERNAS, the national labor survey of Indonesia, provides annual data on the sectoral shares and wages in the agricultural and nonagricultural sectors. Areas under smallholder oil palm cultivation is available annually from the Tree Crops Statistics at the regency level. Based on these two data sources, we compiled a regency-level panel from 2000 to 2015 with annual frequency. For robustness checks, we use PODES (Indonesian village survey) for infrastructure data and a subsample of the Indonesian census for migration data. The UN Food and Agriculture Organization's GAEZ (global agro-ecological zones) database has spatial data on the maximum attainable yield of oil palm and other competing crops across the country at 10 × 10 km resolution (Fischer et al. 2012; FAO 2023). Yields are predicted based on agronomic modeling under prespecified levels of fertilizer use and management conditions.[15] Model inputs include local soil and weather conditions. Spatial data on forest cover were available for 2000, 2005, 2010, and 2012 from Margono et al. (2014). The maps are based on the global forest cover change maps of Hansen et al. (2013), adjusted for the expansion of plantation crops in Indonesia. Data on large-scale oil palm plantations were sourced from Austin et al. (2017). Maps were created by visually interpreting Landsat satellite imagery and retrieved at a 250 × 250 m resolution for 2000, 2005, 2010, and 2015. Only large oil palm estates were mapped owing to the low resolution of the satellite imagery.[16]

[14] In Indonesia, provinces are the highest level of local governance. They are divided into regencies (*kabupaten*) and city-districts (*kotas*). Regencies in Aceh, Papua, and the Maluku islands were excluded from the analysis because data are not available for several years. We included a total of 209 regencies.

[15] We specified low-level input use and rain-fed production.

[16] Satellite data are only available for Kalimantan, Sumatra, and Papua. Since the Tree Crop Statistics data report no significant oil palm expansion in Java, we set oil palm expansion to zero for all regencies in Java.

4. Estimation Strategy

Farm Household-Scale Models

We start by designing models to evaluate our hypotheses at the farm household scale. To test if the additional income from oil palm adoption is generated either through land expansion or through the allocation of freed labor to the off-farm sector, we regress total household income proxied by expenditures on the share of cropland planted with oil palm (hypotheses 1.1 and 2.1). We stepwise add farm size and employment dummies as additional control variables. Clusters of smallholders growing oil palm could correlate with the locations of large oil palm plantations and palm oil mills (Cramb and McCarthy 2016; Gatto et al. 2017). These large-scale plantations and mills could affect employment opportunities and income generation in adjacent villages. In addition, the presence of such plantations might spark land conflicts and decrease tenure security, which in turn influences farmers' investment decisions. Some regencies were also more suitable than others for oil palm, and more central and economical active areas did not lend themselves for oil palm plantations. To address these potential endogeneity bias as much as possible with our dataset, we use either village-level or household-level fixed effects in all our models. The model with village-level fixed effects is specified as follows:

$$T_{kvt} = \beta_0 + \beta_1 OP_{kt} + \beta_2 A_{kt} + \beta_3{}' OF_{kt} + \beta_4{}' X_{kvt} + \mu_v + \gamma_t + \varepsilon_{kvt}, \qquad [4]$$

where T_{kvt} is total expenditure of a household k in village v in year t (in log terms). OP_{kt} is the share of cropland planted with oil palm. A_{kt} is the total farm size, and OF_{kt} includes dummies for off-farm employment. X_{kvt} includes additional control variables such as age, education, and migration background of the household head. γ_t represent year fixed effects. μ_v represents village-level fixed effects. We also employ household-level fixed effects

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models as robustness check throughout the analysis.

To test if farm-household members are more likely to work in general or to take up work in the off-farm sector (hypotheses 1.2 and 2.2), we regress several employment indicators on the share of cropland planted with oil palm. We restrict the sample to working-age individuals between 15 and 65 years. Our reduced-form model of labor supply is specified as follows:

$$OF_{ikvt} = \beta_0 + \beta_1 OP_{kt} + \beta_2{}' K_{ikvt} + \mu_v + \gamma_t + \varepsilon_{ikvt}, \qquad [5]$$

where OF_{ikvt} is a dummy for various types of work, such as employment and self-employment dummies of individual i in household k in village v in year t. K_{ikvt} includes additional controls. We split the sample by gender. We again employ household-level fixed effects models as robustness check throughout the analysis.

Aggregate-Scale Models

To test if oil palm expansion affected employment opportunities at a wider scale, we regress the share of a regency's area planted with oil palm by smallholders on employment rates, sectoral shares (hypotheses 3.1 and 4.1), and wages (hypotheses 3.2 and 4.2). We split our sample again by gender using a panel spanning from 2000 to 2015, which allows us to apply regency-level fixed effects. We opted for five-year differences (2000–2005–2010–2015) because oil palm expansion and production processes are governed by lags and unlikely to be picked up by a year-on-year specification.

Since reverse causality and time-variant unobserved factors could still bias our results, we use an IV approach. This is particularly important because unlike our farm-household data collected in a single province, the regency-level data encompass regions with significant differences in political and societal dynamics. These differences could potentially be linked to both agricultural development and labor market outcomes. Our instrument consists of two components. The cross-sectional geospatial component is the maximum attainable yield of oil palm across the whole of Indonesia, derived from the GAEZ database.[17] We interact the cross-sectional variation in the maximum attainable yield of oil palm across regencies with the annual expansion of the national oil palm area. Edwards (2019a) and Gehrke and Kubitza (2021) already used such an instrument. This interaction term provides a prediction of how much the oil palm area in a regency should have changed solely based on its suitability for oil palm cultivation. Our instrument correlates highly with the actual expansion.[18] Concerning exogeneity, we see no reason why the necessary ecological and climatic conditions for oil palm cultivation should affect the development of sectoral shares and wages over time other than through oil palm expansion. We further assume that the national expansion of oil palm is driven by world market prices and central government policies, not by idiosyncratic regional developments. Since the main islands are spatially segregated, which could lead to potentially different development paths, we also control for regional time trends.[19] Other threats for identification could include differential trends in economic development between oil palm–growing and nongrowing regencies. To address this issue, we control for differential trends across regencies with different initial levels of important proxies for development, such as population density, forest cover, share of households with access to electricity, and share of villages with health infrastructure. The first stage of our fixed effects IV model is as follows:

$$\begin{aligned} OP_{rpt} = {} & \beta_o + \beta_1 AY_r{*}OPA_t + \beta_2 OPA_t + \beta_3{}' X_{rt} \\ & + \beta_4{}' y_t{*}p_p + y_t + \mu_r + \varepsilon_{rpt}, \end{aligned} \qquad [6]$$

where OP_{rt} is the share of smallholder oil palm area of total regency area. In the Appendix,

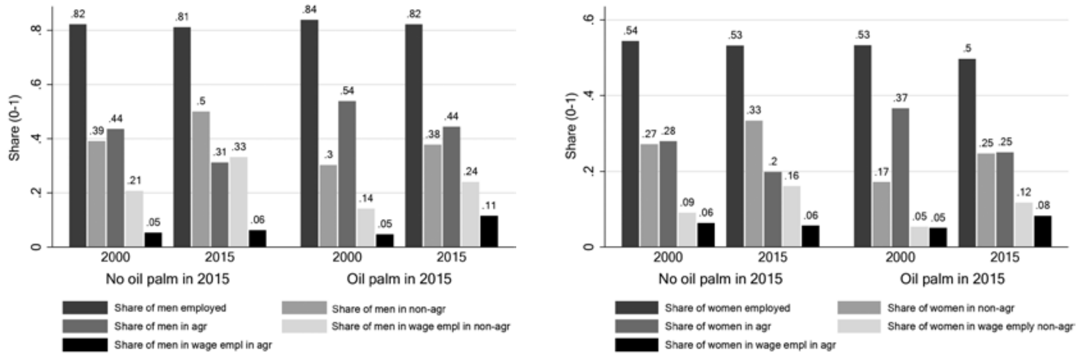
[17] Maximum attainable yield of oil palm is mostly affected by differences in climatic conditions, such as the level and variation in temperature, radiation, and rainfall (Pirker et al. 2016). These conditions are captured by the GAEZ at pixel level.

[18] Pearson correlation coefficient: + 0.305 ($p < 0.01$).

[19] We define five regions including the main islands—Sumatra, Kalimantan, Java, Sulawesi—with their adjacent smaller islands and a fifth category with all other islands.

Figure 1

Gendered Employment Rates at the Regency Level in Indonesia; *left*, Employment Rate and Sectoral Shares of Men; *right*, Employment Rate and Sectoral Shares of Women



Source: SAKERNAS.
Note: Analysis includes 208 regencies; in 2015, smallholders cultivated oil palm in 86 regencies (41%).

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we conduct robustness checks using the expansion of large-scale oil palm estates as an additional control. AY_r is the average max attainable yield for oil palm in each regency r, and OPA_t is the national oil palm area in hectare in year t. X_{rt} includes controls such as average age. y_t are year fixed effects, p_p are region dummies and initial levels of development, and μ_r are regency fixed effects. The second stage is as follows:

$$Y_{rpt} = \beta_o + \beta_1\widehat{OP}_{rt} + \beta_2 OPA_t + \beta_3{}' X_{rt} + \beta_4{}' y_t{*}p_p + y_t + \mu_r + \varepsilon_{rpt}. \quad [7]$$

Y_{rt} represents sectoral shares and wage levels. The other variables are the same as in equation [6]. In addition, we test if infrastructure development and migration could be confounding transmission mechanisms.[20] We use the same IV approach as described in equations [6] and [7].[21]

So far, our models test if changes in the labor market due to oil palm expansion indicate any labor displacement. As outlined in the conceptual framework, these effects depend on the availability of land. To test for this hypothesized effect heterogeneity, we compile data on regencies' forest cover over time based on satellite imagery. This allows us to test whether the expansion of smallholder oil palm is decreasing forest cover, which would indicate an expansion of agricultural land. We also interact smallholder oil palm expansion OP_{rt} with the forest share of each regency in 2000, which serves as a proxy for regencies where the oil palm expansion took place in a relatively land-scarce versus land-abundant setting. Owing to the lack of multiple instruments, we use OLS models with regency-level fixed effects.

5. Results

Descriptive Statistics

Figure 1 shows employment rates and sectoral shares of men (left) and women (right) in 2000 and 2015. We compare regencies with and without smallholder oil palm in 2015. As shown in Figure 1, the decrease in employment rates over time is slightly more

[20] The Indonesian government supported migration movements from the densely populated main island (Java) to the outer islands to obtain laborers for large-scale plantations. These migration movements altered the cultural and sociodemographic composition of the labor force. It is reasonable to assume that migrants are more open to innovation and hence more likely to adopt oil palm and also take up nonagricultural employment.

[21] Our analysis rests on spatial data. In these data, unobserved shocks can be correlated across neighboring regencies. To account for cross-sectional spatial correlation and location-specific autocorrelation, we use heteroskedasticity- and autocorrelation-consistent (HAC) standard errors that are also robust to spatial autocorrelation (Colella et al. 2019). We use a time lag cutoff of 10 years and a distance cutoff of 100 km. Spatial distance is based on the location of regencies' capitals.

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Table 2
Effect of Oil Palm Cultivation on Annual Farm Household Income (2012–2015–2018)

	Village-Level Fixed Effects			Household-Level Fixed Effects		
	Total Household Expenditure (log) (1)	Total Household Expenditure (log) (2)	Total Household Expenditure (log) (3)	Total Household Expenditure (log) (4)	Total Household Expenditure (log) (5)	Total Household Expenditure (log) (6)
Share of oil palm (0–1)	0.294***	0.268***	0.173***	0.232**	0.202*	0.152
	(0.060)	(0.057)	(0.051)	(0.115)	(0.113)	(0.109)
Employed household members (= 1)		−0.605	−0.608		−0.011	−0.008
		(1.034)	(0.916)		(0.033)	(0.033)
Self-employed household members (= 1)		0.256***	0.240***		0.148***	0.148***
		(0.034)	(0.032)		(0.040)	(0.040)
Total farm size (ha)			0.049***			0.038***
			(0.005)			(0.010)
F-statistic	10.853	14.294	21.162	4.533	5.275	6.063
Observations	1,854	1,854	1,854	1,761	1,761	1,761

Note: The data source is farm-household data. Clustered standard errors at the household level are in parentheses. The dependent variable is the log of the total annual household expenditure (1,000 IDR). We control for the age and education of the household head, female-headed households, migrant households, number of women and adults, farm characteristics, distance to province capital, distance to next palm oil mill, employed household members, self-employed household members, total farm size, and year dummies. Additional covariates included in the estimation are in Appendix Table A5.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

pronounced in regions with oil palm. We also observe a shift into agricultural wage employment in regencies with oil palm, particularly for men. In addition, the decrease in women working in agriculture and the shift of women into the nonagricultural sector seem to be more pronounced in regencies with palm oil production. This provides some indication that women and men shifted sectors due to the oil palm expansion. However, aggregate data may mask the large heterogeneity between regions in their transition pathways toward an oil palm–dominated agriculture. Studies from areas formerly dominated by rubber plantations in Sumatra underscore that, for farmers independently switching from rubber to oil palm, only men increased off-farm labor and only on the extensive and not the intensive margin (Chrisendo et al. 2020; Mehraban et al. 2022). In contrast, a study from Kalimantan highlighted significant differences between villages dominated by swidden agriculture compared with oil palm villages, with significantly higher off-farm labor in the latter, for both women and men (Rowland et al. 2022).

Appendix Figure A1 illustrates Indonesia's oil palm expansion disaggregated by producer type. We find an increasing importance of smallholders over time. In 2017, smallholder farmers cultivated around 40% of the total oil palm area. Appendix Table A2 is a detailed description of all variables. Appendix Table A3 shows descriptive statistics for all variables of interest based on the local household surveys. Appendix Table A4 shows descriptive statistics for all variables of interest based on the national data.

Regression Results: Farm Household Scale

In Table 2, we present the effect of oil palm cultivation on farm household total expenditures (equation [4]). Columns (1)–(3) show estimates of models with village-level fixed effects, and columns (4)–(6) show models with household-level fixed effects. Additional control variables at the household and village level are in Appendix Table A5. The results show a consistently positive effect of oil palm cultivation on total expenditure across all specifications.[22] Effect sizes only slightly

[22] Effect sizes are larger in the IV than in the OLS models. Since the Kleibergen-Paap Wald statistic is sufficiently high (> 10), we tend to reject the notion that this is due to a weak instrument. Other reasons could include estimating a LATE and endogeneity bias in the OLS models. In general,

Table 3
Effect of Oil Palm Cultivation on Employment Status of Individuals in Farm Households (2012–2015–2018)

	Working (= 1) (Men) (1)	Working (= 1) (Women) (2)	Working On-Farm (= 1) (Men) (3)	Working On-Farm (= 1) (Women) (4)	Working Off-Farm (= 1) (Men) (5)	Working Off-Farm (= 1) (Women) (6)	Self-Employed Off-Farm (= 1) (Men) (7)	Self-Employed Off-Farm (= 1) (Women) (8)
Village-level fixed effects								
Share of oil palm (0–1)	0.017	−0.159***	0.041	−0.146***	0.151***	0.002	0.070**	0.029
	(0.020)	(0.043)	(0.027)	(0.034)	(0.043)	(0.040)	(0.032)	(0.033)
F-statistic	494.760	89.602	399.988	61.836	66.373	21.417	10.062	8.658
Observations	2,759	2,610	2,759	2,610	2,759	2,610	2,759	2,610
Household-level fixed effects								
Share of oil palm (0–1)	0.076*	−0.078	0.079	−0.046	0.163	4.54e-04	0.165**	−0.048
	(0.043)	(0.094)	(0.069)	(0.085)	(0.110)	(0.080)	(0.069)	(0.062)
F-statistic	538.625	58.762	387.982	37.355	40.157	16.408	7.176	6.762
Observations	2,693	2,548	2,693	2,548	2,693	2,548	2,693	2,548

Note: The data source is farm-household data. Clustered standard errors at the household level are in parentheses. We control for age, age-squared, student, education level, migrant households, number of women and adults in the household, farm characteristics, distance to the province capital, distance to the next palm oil mill, total farm size, and year dummies. Additional covariates included in the estimation are in Appendix Table A6 for village-level fixed effects models and Appendix Table A7 for household-level fixed effects models.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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decrease from column (1) to column (2) and from column (4) to column (5). We hence find some evidence that off-farm activities mediate the effect of oil palm cultivation on total expenditures. However, controlling for total farm size seems to strongly mediate the effect of oil palm cultivation on total expenditures in columns (3) and (6). The findings are consistent with studies that use propensity score matching or panel data models without fixed effects (Euler et al. 2017; Kubitza et al. 2018). Overall, our results support hypothesis 2.1 that under land abundance, the observed positive expenditure effect of oil palm cultivation is partly the result of cropland expansion. However, our results also suggest that off-farm self-employment could mediate the effect of oil palm cultivation to some degree (hypothesis 1.1). In general, because of the increasing land scarcity in Indonesia, it is likely that the labor time saved through adopting oil palm will be increasingly redirected toward off-farm self-employment rather than expanding cropland. This could be also true for our research region in Sumatra, which has experienced extensive deforestation of lowland forests in the past few decades and a rise in land scarcity. This transition is evident in land transactions, as indicated by recall data collected from the surveyed farm households: before 2010, the majority of new plots originated from forested or bush areas, whereas by 2015, new oil palm plots were predominantly situated on land previously used for agriculture (Appendix Figure A2).[23]

In Table 3, we present the effects of oil palm adoption on employment indicators of individual farm household members, again using village- and household-level fixed effects models (equation [5]). Additional control variables at the individual and household levels are in Appendix Tables A6 and A7. Though we find a weak but significant positive effect of the share of land under oil palm cultivation on employment rates of men, employment rates for women are negatively affected in both models, but the effect is only significant in the village-level model (columns (1) and (2)). This is because women are significantly less likely to work on their own farm (column (4)), although the effect is again only significant in the village-level fixed effects model. It is plausible that the effect of increasing oil palm acreage in a household

the output prices for rubber, the main competing crop, were extremely low in 2015, which may have contributed to the large effect sizes (Kubitza et al. 2018).

[23] We note that cropland expansion for individual farms could take place even in land-scarce settings in the case that some farmers are willing to sell their land.

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Table 4
Regency-Level Effects of Oil Palm Expansion on Sectoral Shares of Women (2000–2005–2010–2015)

	Share of Women Working (1)	Share of Women in Non-agricultural Sector (2)	Share of Women in Agricultural Family Labor (3)	Share of Women in Agricultural Wage Labor (4)	Share of Women in Nonagricultural Self-Employment (5)	Share of Women in Non-agricultural Wage Labor (6)
Instrumental variable						
Share of smallholder oil palm area in regency (0–1)	−2.910**	−0.162	−3.188**	0.942	−0.639	0.438
	(1.184)	(0.630)	(1.284)	(0.626)	(0.454)	(0.286)
R-squared	0.155	0.402	0.106	0.072	0.115	0.558
Kleibergen Wald *F*-statistic	23.532	23.532	23.532	23.532	23.532	23.532
Observations	827	827	827	827	827	827
OLS model						
Share of smallholder oil palm area in regency (0–1)	−0.731**	0.339***	−0.613**	−0.011	0.186**	0.114
	(0.348)	(0.129)	(0.301)	(0.190)	(0.093)	(0.075)
R-squared	0.235	0.409	0.216	0.116	0.185	0.564
Observations	827	827	827	827	827	827

Note: The data sources are SAKERNAS and Tree Crop Statistics. The dependent variables are shares ranging between 0 and 1. The IV and OLS estimates are reported with spatial HAC standard errors using a 100 km cutoff. The instrument is the maximum attainable oil palm yield per regency × the national oil palm expansion. We control for the mean age of working-age women, national oil palm expansion, regency fixed effects, year dummies, region trends, initial levels of population density, forest cover, hospital density, and electrification × the time trend. Initial levels are based on data from 2000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

decreases working hours in agriculture for women rather than pushing them completely out of agriculture. Overall, the result matches our plot-level results, which show a strong decrease of women's working hours comparing oil palm and rubber plots (see Appendix Table A1). We do not find that women increase working off-farm in general or engage in nonagricultural self-employment (columns (6) and 8)). We do find, however, that oil palm significantly increases the likelihood of men working in the off-farm sector and engaging in nonagricultural self-employment (columns (5) and (7)). Since we find negative effects of oil palm adoption on women working in agriculture and their employment rates, our results imply to some extent land scarcity (hypothesis 1.2) and the replacement of cropping systems with higher labor intensities. The result could be also driven by preferences for leisure; however, our aggregate-scale models show that these dynamics differ between regions with land scarcity versus land abundance and are likely driven by land access and not preferences for leisure. Our second finding is that although men do not leave agriculture completely—which is reasonable, as our sample consists of farm households where men usually conduct some agricultural work on their farm—they take up additional off-farm work, probably because they spend less time in agriculture (Appendix Table A1). Again, our results reflect the transition in Jambi where land resources over time are becoming scarcer (Appendix Table A2).

Regression Results: Aggregate Scale

Tables 4 and 5 show estimates from a regency panel for the whole of Indonesia between 2000 and 2015 (equations [6] and [7]), including labor households.[24] For robustness checks, we report IV alongside OLS estimates using regency-level fixed effects in both specifications.[25] Column (1) in Table 4 evidences women's employment rates decrease as a result of oil palm expansion, which is similar to the farm-scale models. The observed decrease in employment was mainly driven by the large negative

[24] First-stage results are in Appendix Table A8.

[25] Effect sizes are larger in the IV than in the OLS models. Since the Kleibergen-Paap Wald statistic is sufficiently high (> 10) we tend to reject the notion that this is due to a weak instrument. Other reasons could include estimating a LATE, endogeneity bias in the OLS models, and correcting for measurement error.

Table 5

Regency-Level Effects of Oil Palm Expansion on Sectoral Shares of Men (2000–2005–2010–2015)

	Share of Men Working (1)	Share of Men in Non-agricultural Sector (2)	Share of Men in Agricultural Family Labor (3)	Share of Men in Agri-cultural Wage Labor (4)	Share of Men in Non-agricultural Self-Employment (5)	Share of Men in Non-agricultural Wage Labor (6)
Instrumental variable						
Share of smallholder oil palm area in regency (0–1)	−0.372	−1.771**	−1.053*	2.686***	−1.695**	0.112
	(0.523)	(0.886)	(0.627)	(0.604)	(0.670)	(0.571)
R-squared	0.143	0.345	0.120	−0.009	−0.000	0.567
Kleibergen Wald *F*-statistic	23.312	23.312	23.312	23.312	23.312	23.312
Observations	827	827	827	827	827	827
OLS model						
Share of smallholder oil palm area in regency (0–1)	−0.222*	0.007	−0.401***	0.672***	−0.012	0.012
	(0.122)	(0.203)	(0.135)	(0.160)	(0.133)	(0.126)
R-squared	0.144	0.401	0.150	0.251	0.158	0.567
Observations	827	827	827	827	827	827

Note: Data sources are SAKERNAS and Tree Crops Statistics. Dependent variables are shares, ranging between 0 and 1. IV and OLS estimates are reported with spatial HAC standard errors using a 100 km cutoff. Instrument is the maximum attainable oil palm yield per regency times national oil palm expansion. We control for mean age of working-age men, national oil palm expansion, regency fixed effects, year dummies, region trends, and initial levels of population density, forest cover, hospital density, and electrification multiplied by time trend. Initial levels are based on data from 2000.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

employment effect from the family agricultural sector, which is also in line with our plot-level data and the estimates from the farm-level models (column (3)). These effects are consistent across a large diversity of specifications (see Appendix Tables A10–A18). To some extent, the labor displacement could also have been limited by positive employment effects from the nonagricultural sector. However, only the OLS estimate in column (2) suggests that the expansion of smallholder oil palm area increased the share of women working in the nonagricultural sector.

For men, we observe a significant shift into agricultural wage labor (Table 5, column (4)). The differences to farm-level models could result from using different samples. At the aggregate scale, we also include labor households and cities in regencies and thus also partly control for regional migration. This effect is again stable across a large diversity of specifications (see Appendix Tables A10–A18). We find that men decrease their involvement in family agriculture (column (3)), but the magnitude is smaller compared with the increase in agricultural wage labor. Overall, in contrast to women, we observe no significant and consistent shift out of agricultural activities for men across all models; rather, the opposite is evident. Similar to farm-scale results, these findings are mixed concerning our hypotheses outlined in Section 2. Considering the decreasing labor intensities per hectare for men in oil palm cultivation compared with competing cropping systems, the growing share of men in the agricultural workforce supports hypothesis 4.1. This implies that in the timeframe of our data, Indonesia had still sufficient land resources, which allowed the demand for male labor in agriculture to remain stable or even grow due to cropland expansion. Nonetheless, we also observe a decline in female participation in the agricultural sector, resulting in reduced employment rates. Higher reservation wages could account for this change, but the decline in female employment may also suggest that cropland expanded and cropping systems with higher labor intensities for women were replaced with oil palm (hypothesis 3.1).

Appendix Table A9 includes the results for wages. Overall wages and wages in the nonagricultural sector do not significantly change

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for women or men between 2000 and 2015.[26] We note, however, that while most of the point estimates are positive for the IV models, they are imprecisely measured, which limits further interpretation. We only find some weak evidence in the OLS models that wages for men increased significantly in the agricultural sector, which could be partly driven by the increasing labor productivity in oil palm cultivation. While these results neither support nor reject hypotheses 3.2 and 4.2, we do not observe that wages are significantly falling.

One concern with our analysis is the robustness of our identification strategy. The suitability for oil palm cultivation should be unrelated with other geographic or agroecological characteristics that influence our outcome variables based on trends similar to the national oil palm expansion. We thus interact national oil palm expansion with spatial data on agroclimatic attainable yields from the GAEZ database for the most important crops in Indonesia: rice, maize, coconut, and cocoa (FAOSTAT 2018).[27] Results are shown in Appendix Table A10. The estimates support our main conclusions from Tables 4 and 5. Another concern could be that the effects of oil palm expansion only materialize with some time delay. To test if lagging the explanatory variable changes our results, we reestimated the model using SAKERNAS data from 2002, 2006, 2011, and 2015 and a two-year lag for oil palm expansion (Appendix Table A11). the results are not significantly different from the main results in Tables 4 and 5.[28] Smallholder oil palm expansion is directly linked to large-scale oil palm plantations due to historical government policies, such as the nucleus estate and smallholder scheme. Smallholders also depend on the infrastructure of large-scale plantations, particularly palm oil mills. Our variable might pick up not just the expansion of smallholder oil palm but also large-scale plantations. To address this concern, we merge our dataset with satellite data on the historical expansion of industrial-scale oil palm in Indonesia. Appendix Table A12 shows that our results on the effects of smallholder oil palm expansion are robust to controlling for industrial-scale oil palm.[29]

Effect Heterogeneity and Robustness Checks

Our conceptual framework predicts effect heterogeneity in settings of land scarcity versus land abundance, which could also explain the mixed results in our models. To assess the potential heterogeneity, we interact the regency-level forest share in 2000 with our smallholder oil palm expansion variable. Table 6 shows that in contexts of greater land scarcity, there is a significant negative effect on agricultural family labor for both men and women, presumably because more labor-intensive cropping systems have been replaced by oil palm (column (3)). In column (5), we find that men move from agricultural family labor to nonagricultural self-employment and agricultural wage labor, although the effect is not significant at conventional levels of statistical significance. For women, the decline in employment in family agriculture leads to a significant decline in workforce participation. This confirms hypothesis 3.1 that in land-scarce settings, employment in agriculture decreases, especially for women, and that if the nonagricultural sector does not absorb all

[26] In contrast, Gehrke and Kubitza (2021) found a weakly significant effect of oil palm expansion on women's wages in the nonagricultural sector. However, the study uses a different sample, examining only women aged 15–49.

[27] The ranking is based on harvested area. We did not include rubber since no GAEZ data on attainable yields are available.

[28] We also tested the effect of oil palm expansion on working hours (see Appendix Tables A13 and A14). The effects seem to be concentrated at the extensive margin rather than the intensive margin of labor supply.

[29] Given that palm oil production technologies are similar in smallholder systems and large-scale plantations, male labor productivity is also higher in large-scale plantations. Male laborers switching into agriculture is thus reasonable (Appendix Table A12, OLS model, column (10)). Evidence of case studies exists that large-scale plantations replaced labor-intensive smallholder systems (Cramb and McCarthy 2016). Yet it is unlikely that large-scale oil palm plantations were replacing labor-intensive smallholder systems to the same extent as smallholder oil palm expansion replaced other agricultural land uses for smallholders. This could explain why we find no evidence that women are displaced from agriculture because of the expansion of large-scale oil palm plantations.

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Table 6
Regency-Level Effects of Oil Palm Expansion in Land-Scare and Land-Abundant Settings (2000–2005–2010–2015)

	Share Working (1)	Share in Non-agricultural Sector (2)	Share in Agri-cultural Family Labor (3)	Share in Agri-cultural Wage Labor (4)	Share in Non-agricultural Self-Employment (5)	Share in Non-agricultural Wage Labor (6)
Men						
Share of smallholder oil palm area in regency (0–1)	−0.296	0.589	−1.027***	0.674	0.592**	0.018
	(0.305)	(0.379)	(0.291)	(0.428)	(0.232)	(0.261)
Share of smallholder oil palm area in regency (0–1) × Share of forest cover in 2000 (0–1)	0.218	−1.713*	1.841***	−0.005	−1.777***	−0.020
	(0.680)	(0.988)	(0.706)	(1.027)	(0.631)	(0.673)
R-squared	0.144	0.402	0.159	0.251	0.165	0.567
Observations	827	827	827	827	827	827
Women						
Share of smallholder oil palm area in regency (0–1)	−1.777***	0.108	−1.516**	−0.452	0.276	−0.061
	(0.675)	(0.262)	(0.683)	(0.567)	(0.229)	(0.182)
Share of smallholder oil palm area in regency (0–1) × Share of forest cover in 2000 (0–1)	3.067*	0.678	2.649*	1.292	−0.264	0.512
	(1.606)	(0.599)	(1.524)	(1.307)	(0.495)	(0.437)
R-squared	0.241	0.409	0.220	0.119	0.185	0.564
Observations	827	827	827	827	827	827

Note: The data sources are SAKERNAS, Margono et al. (2014), and Tree Crops Statistics. The dependent variables are shares ranging between 0 and 1. The OLS estimates are reported with spatial HAC standard errors using a 100 km cutoff. We control for national oil palm expansion, regency fixed effects, year dummies, region trends and initial levels of population density, hospital density, and electrification × the time trend. The initial levels are based on data from 2000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

the available labor, employment rates decline, too. In contrast, family labor in agriculture does not decrease in land-abundant settings. Women do not leave the labor market, and men do not shift into nonagricultural self-employment. This is in line with hypothesis 4.1 that in land-abundant settings, demand for agricultural labor will not decrease and may even increase, especially for men.

Overall, we found robust and consistent evidence that the expansion of oil palm, on average, did not lead to a significant displacement of male labor from the labor market in general. However, we find that the smallholder oil palm expansion led to male labor reallocating toward agricultural wage labor away from agricultural family labor and the nonagricultural sector. Our conceptual framework predicts such results if oil palm expansion is associated with a general expansion of agricultural land. Satellite imagery shows that half of Indonesia's forest loss between 2001 and 2016 is due to the expansion of large and small-scale plantations (Austin et al. 2019). While other agricultural land uses and grassland/shrubland are also converted to oil palm, forest conversion plays a key role (Krishna et al. 2017b). We expect that smallholder oil palm expansion is negatively related to forest cover in Indonesia. In Appendix Table A19, we estimate the effect of smallholder oil palm expansion on forest cover at the regency level, using data from 2000 to 2012. A 1-unit area increase in smallholder oil palm cultivation is associated with a loss of 0.72 units of forest cover. This confirms that smallholder oil palm expansion is associated not only with conversion of other crops but also with forest loss and a general expansion of agricultural land.

In an additional robustness check, we control for several infrastructure variables, such as roads, schools, and electricity at the regency level, using PODES data.[30] To assess the effect of potentially confounding variables, we

[30] To merge the different datasets, we had to restrict the time span to 2001–2014 with three-year differences. The results hardly differ from the earlier ones shown in Tables 4 and 5 for the five-year differences.

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must use a fixed effects specification without an IV as in the OLS section of Table 4. Appendix Table A15 shows the results for the period adjusted to data availability without controlling for infrastructure. Appendix Table A16 includes the infrastructure variables as additional controls. The results are qualitatively similar to the estimates in Appendix Table A15, which supports our argument that the results are not primarily due to infrastructure development.[31]

As discussed, one concern with the validity of our estimates stems from the fact that oil palm expansion correlates with migration flows. We control for migration status in all household- and individual-level regressions. Moreover, controlling for the share of migrants at the regency level does not alter the effect of oil palm expansion on sectoral shares, as additional robustness checks indicate (see Appendix Tables A17 and A18).[32] These tables support the observation that only some population groups enter the nonagricultural sector. Men enter agricultural wage labor, but women also switch into the nonagricultural sector, which is in line with the gendered productivity differentials between oil palm and alternative crops.

6. Conclusion

Several new labor-saving land uses and technologies have been introduced and promoted in the rural areas of developing countries, but their potential labor-displacing effects have received little attention in empirical research. This article documents the labor market effects of a labor-saving land use—the expansion of oil palm among smallholder farmers in Indonesia—both at the farm household and at the national scale. Our results suggest that oil palm expansion has contributed to rising income levels for Indonesian smallholder farmers but has significantly decreased the demand for agricultural labor per unit area. At the same time, oil palm expansion, particularly into forestlands, has led to new employment opportunities in the agricultural wage labor sector, which has buffered most of the adverse labor market effects for vulnerable groups, such as rural, landless labor households. For women, the results are less positive from a labor market perspective, and we observe decreasing labor force participation among women due to a large drop in agricultural family work.

Conceptually, if wages and output are fixed, a labor-saving land use change can decrease labor demand in the economy, affecting less productive population groups and groups with limited access to land and capital. But in Indonesia, output was not fixed, and further cropland expansion was possible. At the farm scale, a considerable share of the positive income effect of oil palm cultivation is generated through cropland expansion. This was confirmed at the national scale, where the results indicate that oil palm expansion significantly increased deforestation.

The expansion of cropland compensated for some of the labor-displacing effects of oil palm and increased the demand for agricultural wage labor, especially for men. Indeed, we find evidence that men reallocated part of their time to agricultural wage labor. Besides direct labor demand effects, the literature suggests that oil palm contributed to income growth and increased investments, leading to local demand effects and a boost to the nonagricultural sector (Edwards 2019b; Gehrke and Kubitza 2021; Kraus, Heilmayr, and Koch 2021). For women who are generally less likely to work in the oil palm sector compared with other crops, local demand effects and a growing nonagricultural sector could have absorbed female labor that was freed from agriculture. However, we find no robust evidence that women increased their involvement in the nonagricultural sector at the farm or national

[31] We observe in line with our expectations that men are more likely to work in agricultural wage employment and that women are less likely to work in agricultural family labor with smallholder oil palm expansion. The results also show an increase for women working in agricultural wage employment, which we have not observed in any other regressions. However, these are OLS results, and the effect is no longer significant in our preferred IV models. In addition, two- or three-year differences are not ideal as oil palm expansion and production processes (oil palm becomes productive after approximately three years) are governed by lags and unlikely to be picked up by this specification. We opted for five-year differences in our main models (2000–2005–2010–2015).

[32] We use a census subsample to obtain data on migration. We use census data for 2000 and 2010. The baseline results confirm our findings in Tables 4 and 5.

scales. Owing to the drop in family agricultural employment for women, female labor participation decreased substantially. This trend is worrying, and its implications should be the focus of further research.

Our results also suggest that these effects are highly heterogeneous between regions with scarce land resources compared with regions with abundant land resources. In settings with abundant land resources for agricultural expansion, as proxied by forestland, we find that women face neither a decline in employment in family agriculture nor a decline in general employment rates. In contrast, the decline in female agricultural employment is quite strong in regions with scarce land resources. This effect heterogeneity may also explain heterogeneity between different case studies in different regions but also differences across time, as the substantial positive income effects of the oil palm expansion, particularly for smallholder farmers, are likely to be more muted in the face of population growth and reduced availability of land for agricultural expansion.

In this context, it should be stressed that these beneficial economic effects for rural laborers occurred largely at the expense of natural ecosystems, particularly forestland. Direct countermeasures to prevent deforestation could include increasing the labor intensity per unit of land. However, measures in this direction would be limited in scope since the marginal product of labor in oil palm cultivation will fall rapidly with increasing labor intensity. Alternatively, restricting further forest encroachment and improving the rural labor market opportunities in general would force new oil palm adopters to reallocate more of their saved labor to the nonagricultural sector. Our results suggest that without land expansion by farm households, rural laborers without sufficient land to operate their own farms, particularly women, find little working opportunities in smallholder agriculture and would face increasing competition in the nonagricultural labor market. This presents a fundamental trade-off for policy makers. To manage labor savings in agriculture, we suggest that improving tenure security for agricultural and forest lands might have to go hand in hand with nonagricultural employment initiatives focusing on marginalized rural population groups. Isolated interventions might entail undesirable social effects.

Our results underscore that the economic, social, and environmental effects of labor savings in agriculture must be closely interpreted against the backdrop of land abundance and access to labor markets. While the Indonesian case (and historical data from agricultural expansion in industrialized countries) shows that labor-saving technologies can be economically beneficial, this may not be the case in settings with scarce land resources or limited access to the nonagricultural sector. Furthermore, if the economic benefits of labor-saving technologies are not widely distributed and accrue only to small sections of society, such as owners of large-scale plantations, local demand effects could be substantially smaller and labor displacements more widespread. Besides these economic and social concerns, implementations of labor-saving technologies in settings with weak land regulation must be conducted with caution to preserve remaining natural ecosystems.

Acknowledgments

We thank Peter Pütz, Thomas Kneib, and Kira Urban for helpful comments. This study was funded by the Deutsche Forschungsgemeinschaft (German Research Foundation/DFG, project 192626868) in the framework of the collaborative German-Indonesian research project CRC990. Thomas Kopp thanks the DFG for funding within project KO 5269/1-1. Christoph Kubitza thanks the Land Matrix Initiative Phase 3 for funding (Swiss Agency for Development and Cooperation (SDC; grant 81057843), the German Federal Ministry of Economic Cooperation and Development (BMZ; grant 2018.0130.7), and the European Commission (grant FOOD/2019/407–513).

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